Dymanic Data Prefetching with Prediction-by-partial Match Approach for Route Guidance

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Abstract

Mobile devices can provide the user location-dependent information services (LDISs), enhanced by prefetching the related information along with the route guidance based on user mobility mode. The current prefetching approaches are based on static assignments of probabilities of changing directions, hence the overall cache-miss for users are not reduced by the mobilities of the individuals. In this paper, we adopt the Prediction-by-Partial Match (PPM) technology to predict the best possible mobility of a user elaborated from his/her past history, to prefetch the most useful information for their LDIS. In our experiments, it is proven that our approach is more effective than Persone's approach for improving the rate of cache-miss and the energy consumption at most cases of prefetching data to get LDIS through on a route.

Keywords

Cache-miss; Data Prefetching; Location-depedent Information Services;Pediction-by-particail Match; Route Guidance

Introduction

Based on the benefits of mobile computing and network, more LDISs are currently desired by users. To conquer the deficiency of getting location-dependent information caused by cache-miss, prefetching the related data is currently widely adopted. However, those approaches are based on static assignments of probabilities of changing directions. Hence, the overall cache-miss for users is not reduced by the mobility of the individual. In this paper, we adopt the Prediction-by-Partial Match (PPM) technology to predict the best possible mobility of a user by the situation based on his past history, to prefetch the most useful information for his LDIS.

In general, mobile devices could request a Base Station (BS) to get the information about the particular location from the remote server. However, the BS may be the bottleneck of the network caused by the quality of communication, so that prefetching the data is necessary for mobile devices in order to hold enough location-based information. On the other hand, too many prefetching would cause too much energy consumption which could overload mobile device's capability.

Some well-known prefetching approaches have been applied to reducing the retrieval time of location-based information for mobile devices. Among them, one method, proposed by Persone and Grassi, improved the efficiency of prefetching data for the route guidance services according to the static mobility mode of users. However, the static model cannot fit the individual user behavior without seams, such as the probabilities of cache-miss, which may be caused by lost ways and directions and not be reduced.

To enhance the efficiency of data prefetching, we found the dynamic mobility model for the individual user useful. Base on the more seamless mobility model of a user, the prefetched data may match his requirement, hence reduce the number of times to link the remote server. Consequently, a large amount of navigation on mobile network can be reduced, and this will lead to more effective energy consumption for mobile devices.

In this paper, we deploy a PPM method to construct a dynamic individual mobility model for the users based on their past accessing history. At the same time, the related prefetching actions are dynamically applied to the requests of the user according to the related ultimate models. Obviously, when a cache-miss happened, the proposed method may

immediately adjust the individual mobility model, which is used to improve the performance of prefetching for the location-dependent information.

In general, our approach proposed in this paper used two methods to improve the efficiency of data prefetching. First, we incrementally construct the mobility models with PPM. Second, some patterns knowledge in the constructed PPM can further help us prefetch users' locations. Hence, the process of a sequence prefetching to support LDISs on a route can be more effective, and improve the energy consumption for mobile devices.

The following text in this paper is organized as follows. We first outline the literatures, including the route guidance service systems, mobility model Persone proposed and prefetching mechanisms in Section II. In Section III, we present how to simulate the users' path, and a PPM-based data prefetching mechanism. We also present the expressions to evaluate latency and energy consumption when prefetching techniques are used. Then, in Section IV, some comparisons of performances between our approach and those of applying static mobility models are explained. Finally, conclusions of our approach and some possible extensions in the future are provided in Section V.

Related Work

Route guidance has been popularly used in traffic where the destination is specified by a user who may not know the related routes from his location to a destination. Usually, this request can be severed with Global positioning systems (GPS) or some analogical systems built to support mobile computing. To maintain the correctness of the route of user moving, the location-based information along with the route should be captured, then list the preferences of branches for users to make decisions for the desired directions. However, due to the delay of information in mobile network, the related location-based information is usually necessary to be prefected in order to provide enough time to users before the decisions have been made.

Persone has proposed a probabilistic approach to prfetch the location-based information to serve route guidance. For example, in Fig. 1, where the variable x represents the current position of user, the location-based data are captured from the neighbours (directions to end or front) shaded by the gray area, which may be fetched from the remote server, and will be stored in the cache of mobile devices to serve the current route service.

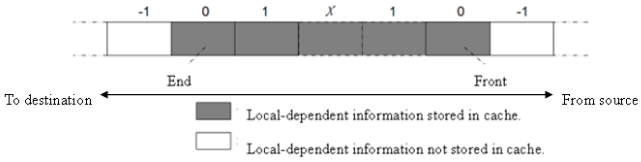

FIG. 1 PERSONE DATA PREFETCHING STRATEGY

According to the model mentioned above, two approaches of fetching the location-dependent information can be derived: demand-driven caching and anticipated prefetching. In the first approach, the related information is acquired as users enter a new white area in which a cache-miss occur, e.g., the position x is changed to -1. On the other hand, the second approach acquires the related information proactively on the position 0. The amount of the fetched information can be specified by users, e.g., the number of units is 5 in Fig. 1.

In order to find the regularity of the user's mobility, Persone exploits the roadway structure of urban region to define the environment to provide the guidance service for the user, adding the probability for the routes similar to the proposed user mobility model as shown in Fig. 2. Persone define the probability g which means the user leaves the present region (grey area), the probability c means the user leaves according to the original way, the probability a means the user moves backward according to the original way, and the probability b means the user moves forward according to the original way. Therefore, the probability of the user taken to present ways to move backward is gca, while the probability of the user taken to present way to move forward is gcb, the probability of the user that remains in place is 1-g, and the probability of the user meeting the branch road to leave the present way is g(1-c).

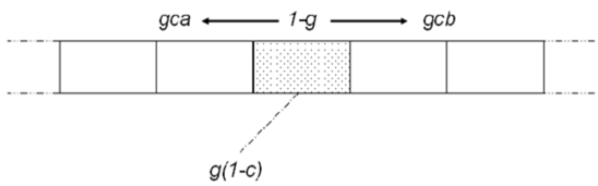

FIG. 2 PERSONE DEFINITION'S MOBILITY MODEL

Based on the reference of persone definition's mobility model and observation of the user route guidance service in use, we can summarize the two cases adopted in the route guidance service are the possible axis of movement, as shown in Fig. 3.

1. Complete consistent route: When user's axis of movement is completely consistent with system planning's route, we call completely consistent

route. When the user's is unfamiliar with the roads, perhaps to a strange environment, user needs to move in accordance with the system defined routes.

2. Partial consistent route: When user's route is not fully consistent with system planning, we call this partial consistent route. Users under guidance may detour due to road condition and system planning route and may not fully respond to real time. For example, when road construction, traffic control, traffic accidents, and the traffic signal indication are not clear, users may need to take a different route to the system default.

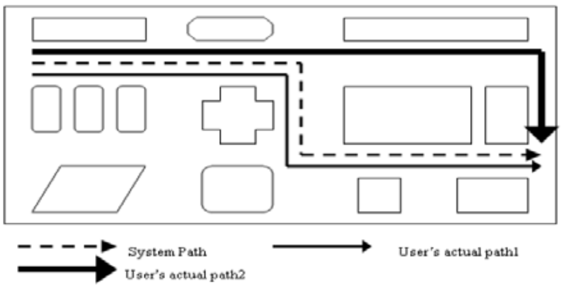

FIG. 3 USER'S POSSIBLE AXIS OF MOVEMENT

The study also shows about 30% of the user will not follow complete instruction, therefore a functioning route guidance system must be established to provide the user with reliable information; otherwise, a user may refer to the actual road situation to determine the following routes rather than follow the guidance device.

Markov chain is probably established in A.D. 19th century by Russian scientist Andrei Markov (1856-1922). It is a special state probability, used in extrapolating the future. For data mining, the Markov chain is often used on user behavior prediction. The significance of the probability lies in either the next possible event or the probability based on the state of previous event.

For example, $<b_1, b_2, \ldots, bn> \rightarrow <b_{n+1}>$ is a Markov chain and $<b_1, b_2,\ldots, bn>$ is how a user sequentially extract data blocks b1 to bn. We can then forecast that this user access the next data Pn+1 where conditional probability is $P(b_{n+1} | b_1, b_2, \ldots, bn)$. If the calculation of the conditional probability is decided before n data, then n can be seen as orderly. Assume a Markov chain $<b_1, b_2> \rightarrow <b_3>$, and we can utilize the user to access from data b_1 to the b_2 to forecast the probability of data b_3 is to be used. This is called 2-order Markov predictor.

The PPM technology may be used to establish 1-order, 2-order,…, k-order Markov predictor. As shown in Fig. 6, it's a partial metropolis streets diagram, assume data set Q = {A, B, C, D, E, F} and user's first access this data set S is <A, B, C>, and 2[nd] access S is <A, D, F>. The PPM calculation process that establishes this access procedure a biggest order is 2 level PPM model, and sets up Trie tree by the special retrieval to express it, as shown in Fig. 4.

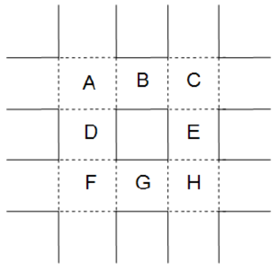

FIG. 4 PARTIAL METROPOLIS STREETS

The node from material access procedure S. from which establishes the rule where access procedure preceding data is deemed to be father node, and root node R is also each data's father node, which simultaneously calculates the appearance of each node various times. Above all, the increase in first data A is the root node R child node, and presents the number of times is 1. Then the increases in second data B is the node A child node, simultaneously also increases another B node for the root node R child node, both all for the first appearance. Equally, then the increases in third data C is the node B child node, simultaneously also increases another C node for the root node R child node, and both of them appear for the first time. The calculation of forth data A simultaneously should also increase another A node for the node C child node, but the root node R child node A left sub-tree arrived at the second-order level the altitude, therefore only in root node R child node A, but the root node R child node already had a node existence. Therefore, present root node R child node A will be transformed into 2, without establishing a A node for root node R. Finally, the way by which fifth data D and sixth data F increase is similar to that of the data B the data C. According to the similar calculation rule for each data establishment node, Fig. 5, a biggest order of 2 level PPM model, will be subsequently obtained.

The Observation of Fig. 5 PPM model sets up the procedure that can be expressed as Fig. 6 algorithm. Algorithm Prediction-by-Partial-Match gathers the PPM model utilizes user's access pattern to which the S construction corresponds. The line 1 starts to return

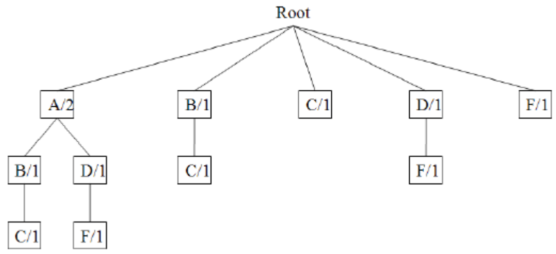

FIG. 5 A BIGGEST ORDER IS 2 PPM MODELS

to the circle to gather in S each data to the pattern to make processing return to the circle judgement using the line 2 to gather the S data that have already have been established in the node. If this node already existed, then calculates the number of times when this node appears. Otherwise, a new data will accordingly become a new child node. The leaf node has been repeatedly calculated until the tree root node.

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Objective: Build a prediction model based on the access patterns of the users.
Input: The trie structure T, representing the prediction model of order m
       construed so far, and a set S of events deriving from the users.
Output: The updated prediction model.
Prediction-by-Partial-Match(R)
1: for every event R in S
2:   for length j = m downto 0
3:     if currentContext[j] has child-node C representing event R
4:       node C occurrenceCount = occurrenceCount + 1
5:       currentContext[j + 1] = node C
6:     else
7:       construct child-node C representing event R
8:       node C occurenceCount = 1
9:       currentContext[j + 1] = node C
10:    currentContext[0] = root node of T
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FIG. 6 PPM ALOGRITHM

The retrieval of PPM model by which Trie tree really is the supposition that wants the pattern length to retrieve as W, inputs the PPM model data quantity is the N, the biggest order number of PPM model is k, searches for the data in the PPM model the time order of complexity is O($\frac{W}{k}$). The PPM model that needs the memory space is O(2^k *N* $\frac{W}{k}$). Renew the time order of complexity in PPM model is O($\frac{W}{k}+2^k$).

Dynamic PPM-based Data Prefetching Mechanism

In this section we will explain our research how to use the pattern to establish data prefetching set, and compare the performance between the PPM-based data prefetching strategy and Persone provided one.

Data Prefetching Set

According to the PPM model, we could forecast possible sequential pattern which the user may adopt in the future. Suppose the data set Q = {A, B, C}, a pattern meaning that a path is combined by some data, e.g., <A, B>、<A>. Take Fig. 7 PPM model for example. The root node R may extrapolate the following 11 sequential patterns and each item of sequential pattern support.

Dependence on each sequential pattern extrapolates each item of rule as well as each item of rule confidence again. Support is some item of sequential pattern the proportion which occupies all sequential patterns. Each item of rule is all divided into the antecedent and the consequent (right arrow left side expressed that antecedent, right arrow's right side represents consequent), we suppose that the set consists of all the sequential patterns F = {S_1, S_2, …, S_n}, and the number of all are |F| and the number of sk are | S_k |, its formula is:

$$\text{support(sk)} = \frac{|s_k|}{F} * 100\% \qquad (1)$$

Confidence represented in rule is to forecast the consequence by the antecedent the probability, while antecedent supports and the entire item of sequential pattern support proportion, the formula of the rule r<S_1, S_2, S_3, …, S_i> → <S_{i+1}> is:

$$\text{Confidence(r)} = \frac{\text{support}(< s_1,\ldots,s_i,s_{i+1} >)}{\text{support}(< s_1,\ldots,s_i >)} *100\% \qquad (2)$$

Take the rule r<A, B> → <C> for instance. <A, B > altogether appeared in complete 11 item of sequential pattern two times, therefore pattern <A, B> support are 18%(2/11) approximately. Equally, <A, B, C> altogether appeared in complete 11 item of sequential pattern one time, therefore pattern <A, B, C> support are 9%(1/11) approximately. Then inference of rule r<A, B> → <C>, extracts this rule the confidence standard:

$$\text{Confidence(r)} = \frac{\text{support}(< A,B,C >)}{\text{support}(< A,B >)} *100\%$$

$$= 50\%$$

This means under 50% confidence, forecast the user extract sequential pattern <A, B >, they will continue to extrct sequential pattern <C>. Using each user's moving patterns history, we hoped to establish individual PPM model for each user. Inferring each user's pattern knowledge can establish each kind of size again threshold, which namely could acquire each

user's different individual prefetching data set.

Take Fig. 4 for example, each character represents a different region. We supposed that 2-order PPM model for user1, as shown in Fig. 5. Then, we use this model to project user1's individual pattern knowledge, as shown in Table I.

TABLE 1 USER1'S INDIVIDUAL PATTERN KNOWLEDGE

No.	Sequential pattern	Support (%)	Rule	Confidence (%)
1	<A>	45.45	X	X
2	<B>	36.36	X	X
3	<C>	27.27	X	X
4	<D>	36.36	X	X
5	<F>	27.27	X	X
6	<A, B>	18.18	<A> → <B>	40.0
7	<A, D>	18.18	<A> → <D>	40.0
8	<B, C>	18.18	<B> → <C>	50.0
9	<D, F>	18.18	<D> → <F>	50.0
10	<A, B, C>	9.09	<A> → <B, C> <A, B> → <C>	20.0 50.0
11	<A, D, F>	9.09	<A> → <D, F> <A, D> → <F>	20.0 50.0

By setting different confident threshold, we would acquire user1's different individual prefetching data set. In the experiment, we hoped that using each user's different route to establish PPM model for each user, because of each user's historical route, PPM model can be established again. This research discusses PPM model under each kind of confidence, prefetching data set to route guidance service influence, appraising this research to propose that the PPM-based data prefetching strategy, as compared in Persone's data prefetching method whether a better effect will be displayed.

Cache-miss Analysis

To analyse the matching between the user's actual route and system planning's route, see Fig. 7, where the two types of routes are shown by solid and dashed lines without arrows respectively. We assume the situation that the user travelled L regions, where the probability of the user completely or not followed by the system planning's route is P_f and $(1 - P_f)$ respectively. In addition to considering the situation of corner turning, four cases can be explained as follows:

- Case 1: In this case, the user completely follows the system planning's route and no corner turning happened, represented by the piece from the node X_{i+1} to the node X_{i+2} in Fig 8. And, the number of region1 would be $P_f * L * P_s$ regions .
- Case 2: In this case, the user completely follows the system planning's route where a corner turning occurred, represented by the piece from the node X_{i+1} to the node X_{i+2} in Fig 8. And, the number of region1 would be $P_f*L*(1 – P_s)$ regions.
- Case 3: In this case, the user partially follows the system planning's route and a corner turning might be likely to happen, represented by the piece from the node Xi to the node X_{i+1} in Fig 8. And, the number of region1 would be $(1- P_f)*L* P_x$ regions.

1) Case 3-1: The direction of system planning's route is linear, indicating that both the node Xi and the nodeX$_{i+1}$ are under the same line (e.g., user from the node X_3 to the node X_4). But it has the probabilityP_y which the user not follows system planning's route because the route is not linear. Then, we generalize that $(1-P_f)*L*P_x*P_y$ regions belong to user1's first path path1 is A → B → C, user1's second path path2 is A → D → F. And take these two ways to establish this individual case.

2) Case 3-2: The direction of system planning's route is not linear, indicating that both the node Xi and the nodeX$_{i+1}$ are under the same line (e.g., user from the node X_4 to the node X_5). But it has the probability $1-P_y$ that the user not follows system planning's route because the route is linear. Then, we generalize that there have $(1-P_f)*L*P_x*P_y$ regions belong to this case.

- Case 4: In this case, the user partially follows the system planning's route and a corner turning definitely will happen, represented by the piece from the node Xi to the node X_{i+1} in Fig 8. And, the number of region1 would be $(1-P_f)*L* (1-P_x)$ regions.

Although Persone indicates that when a user meets a intersection, the route may be changed, but lacking in clear forecasts of the direction may lead to the cache-miss. We define the route when a user meets an

intersection conditions to happen cache-miss as shown in Fig. 8a、Fig. 8b、Fig. 8c and Fig. 8d.

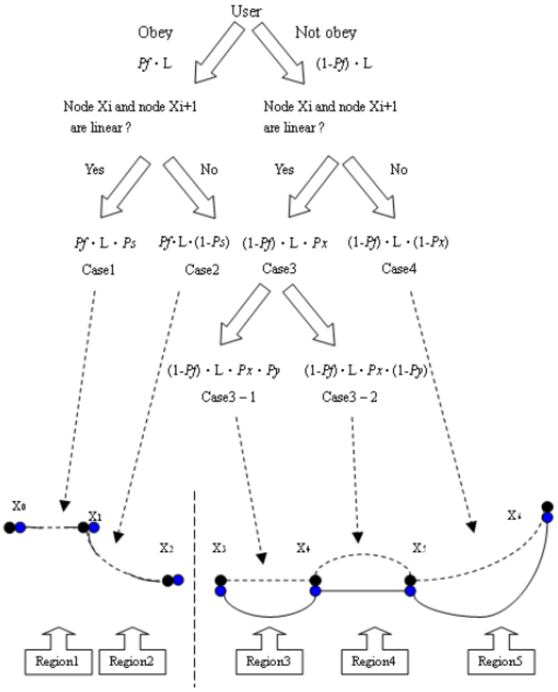

FIG. 7 USER'S LOCUS ANALYSIS FLOW CHART

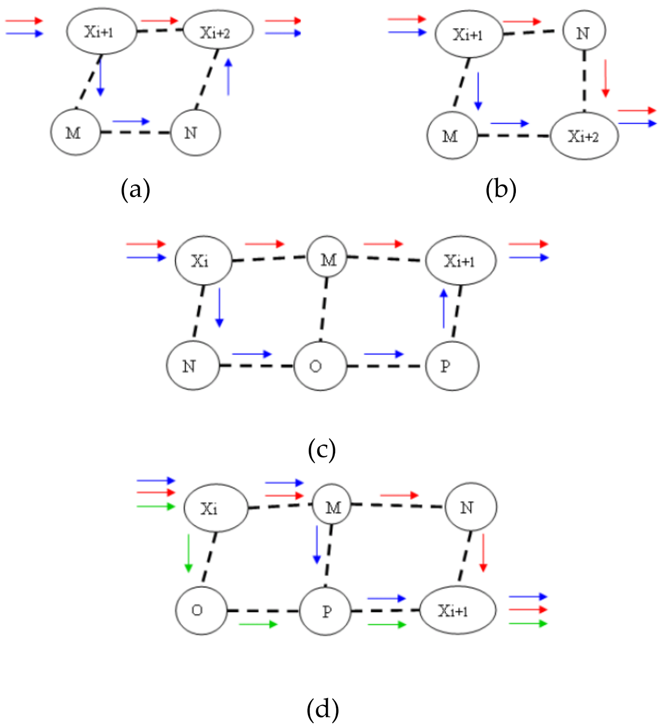

FIG. 8 RELATIONS FOR SYSTEM PLANNING'S ROUTE AND THE USER'S ACTUAL ROUTE.(A) USER FOLLOWS THE GUIDANCE ROUTE, BOTH THE NODE X_{I+1} AND THE NODE X_{I+2} ARE UNDER THE SAME LINE. (B) USER FOLLOWS THE GUIDANCE ROUTE, BOTH THE NODE X_I AND THE NODE X_{I+1} AREN'T UNDER THE SAME LINE. (C) USER NOT FOLLOWS THE GUIDANCE ROUTE, BOTH THE NODE X_{I+1} AND THE NODE X_{I+2} ARE UNDER THE SAME LINE. (D) USER NOT FOLLOWS THE GUIDANCE ROUTE, BOTH THE NODE X_I AND THE NODE X_{I+1} AREN'T UNDER THE SAME LINE.

In addition, we also define the set of the number to turn a corner is U, in order to represent the relations conveniently for system planning's route and the user's actual route, we use U(path1/path2) to replace ones, path1 is system planning's route and path2 is the user's actual route. In Fig. 8a and Fig. 8b, both means that user follows the guidance route, regardless of red or blue one belonging to path1 and path2. On the other hand, in Fig. 8c, if the red one is path1, then the blue one is path2, vice versa. In Fig. 8d, there are three kinds of situations, assuming that one of three is path1, and then, the others are path2, vice versa. Take U(X_i, M, X_{i+1}/ X_i, N, O, P, X_{i+1}) in Fig. 8c for example, <X_i, M, X_{i+1}> is system planning's route and <X_i, N, O, P, X_{i+1}> is the user's actual route, we get five relations of the number of cache-miss as follows:

1. Referring to Fig. 8a, even in the case of no corner turning for nodes X_{i+1}, X_{i+2}, the system would suggest the two routes shaded by red and blue respectively. From which, we got U(X_{i+1}, X_{i+2}/ X_{i+1}, X_{i+2}) = 0 and U(X_{i+1}, M, N, X_{i+2}/ X_{i+1}, M, N, X_{i+2}) = 4 for red and blue paths respectively. To compare the performance of Persone's and our approach, we digest the minimum case where U_1 = 0, corresponds to the number of corner turning of Case1 in Fig. 7.

2. Referring to Fig. 8b, where there is a corner turning for nodes X_{i+1}, X_{i+2}, the system would suggest the two routes shaded by red and blue respectively. From which, we got U(X_{i+1}, N, X_{i+2}/ X_{i+1}, N, X_{i+2}) = 2 and U(X_{i+1}, M, X_{i+2}/ X_{i+1}, M, X_{i+2}) = 2 for red and blue paths respectively. To compare the performance of Persone's and our approach, we digest the minimum case where U_2 = 2, corresponds to the number of corner turning of Case2 in Fig. 7.

3. Referring to Fig. 8c, it can be divided into two kinds, Case3-1and Case3-2 respectively. If the red one is path1, then another one belongs to path2, we could derive U_{31}(X_i, M, X_{i+1}/ X_i, N, O, P, X_{i+1}) = 4 and mapping to Case3-1. On the contrary, if the blue one is path1, then another one belongs to path2, we could derive U_{32}(X_i, N, O, P, X_{i+1}/ X_i, M, X_{i+1}) = 0 and mapping to Case3-2.

4. Referring to Fig. 8d, we select one out of three paths to be path1, and choose one from the remaining to be path2, producing six kinds of

situations. To compare the performance of Persone's and our approach, we digest the minimum case where $U_4 = 2$ corresponds to the number of corner turning of Case4 in Fig. 7.

In general, we refer the all above-mentioned cases, $U(C_1)$ as the number of corners in Case1, $U(C_2)$ is the number of corners in Case2, $U(C_{31})$ is the number of corners in Case3-1, and $U(C_{32})$ is the number of corners in Case3-2. Then, we can obtain the number to turn a corner K as

$$K = U(C_1) + U(C_2) + U(C_{31}) + U(C_{32}) + U(C_4) \quad (3)$$

From the above equation, we could commence its individual listed as follows:

$U(C_1) = U_1 * P_f * L * P_s$,

$U(C_2) = U_2 * P_f * L * (1 - P_s)$,

$U(C_{31}) = U_{31} * (1-P_f) * L * P_x * P_y$,

$U(C_{32}) = U_{32} * (1-P_f) * L * P_x * (1-P_y)$,

$U(C_4) = U_4 * (1-P_f) * L * (1-P_x)$,

We simplify the formula (3) as

$$K = 2L[(1-P_f P_s) - P_x(1-P_f)(1-2P_y)] \quad (4)$$

In other words, if we adopt the Persone's approach may condition K times cache-miss.

We observe user's historical route, records region which migration of route each user passes through, because of the PPM-based data prefetching mechanism means that, the analysis of some pattern knowledge may contribute to these pattern knowledge to establish PPM model for each user, and then find the biggest probability from the PPM model for a user to refer to. Besides, we also invents how the route guidance can be utilized when the route guidance service is consistent with actual situation, we induce two kinds of users' use when the route guidance service is the possible axis of movement, as shown in Fig. 3.

When the cache-miss happened, we will forsake the pattern knowledge and choose the bigger one from PPM model again. We define the number of cache-miss time as the system planning's route different from the user's actual route. Take Fig. 9 for example, we suppose the first time to choose the system planning's route is from the node A to the node E and its probability is P_0, when user changes the route in node B, we adopt the PPM-based approach to choose the biggest probability pattern knowledge from PPM model and the probability of the route is P_1, it is called the first cache-miss. Equally, when user change the route in node B, we adopt the PPM-based approach to choose the biggest probability pattern knowledge from PPM model again and the probability of the route is P_2, we refer to it as the second cache-miss. Finally, three times cache-miss took place in four regions. Thus, we suppose a user changes I times in the travel, and the probability of each system planning's route is Pi, so we can present the I as follows:

$$I = (1-P_f)*L \quad (5)$$

Whatever approach is chosen, we both define the expected value to be the probability of the each system planning's route multiply the number of cache-miss and compare the value of two approaches, if the value is bigger, the possibility of the cache-miss bigger. Therefore, the expected value of Persone's approach is as follows:

$$2\sum_{0}^{n} P_i * L * [(1-P_f P_s) - P_x(1-P_f)(1-2P_y)] \quad (6)$$

The expected value of PPM-based approach as follows:

$$\sum_{0}^{m} P_j * L * (1-P_f) \quad (7)$$

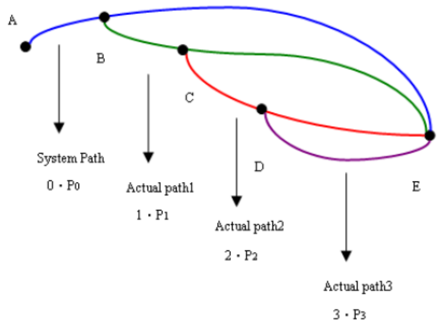

FIG. 9 PPM-BASED DATA PREFETCHING MECHANISM DIAGRAM

On the side, we discuss two special cases, which can separate the direction of the user's actual route to linear and not linear, and can be explained follow as:

- Case 1: The direction of the user's actual route keeps with linear at all.

1) Case 1-1: The user absolutely followed with system planning's path and the direction of system planning's route is not linear at all, the performance we suggest to adopt our approach is better than Persone's one.

2) Case 1-2: The user absolutely followed with system planning's path and the direction of system planning's route is not linear, but the user doesn't follow system planning's route because the route is linear, the

performance we suggest to adopt Persone's approach is better than ours.

- Case 2: The direction of the user's actual route is not linear at all.

1) Case 2-1: The user followed with system planning's path and the direction of system planning's route is not linear at all, the performance we suggest to adopt our approach is better than Persone's one.

2) Case 2-2: The user doesn't conform to system planning's path and the direction of system planning's route is linear, but the user not follows system planning's route that cause the route is not linear, the performance we suggest to adopt our approach is better than Persone's one.

3) Case 2-3: The user doesn't comply with system planning's path and the direction of system planning's route is not linear, but the user not follows system planning's route that the route is not linear, the performance we suggest to adopt our approach is better than Persone's one.

Performance Metrics

This research aims to carry on the analysis parameter showing like, when the user utilizes the service. We take the information average latency Tload and electric power consumption Ttot as the evaluation prefetches efficiency targets.

The average latency to get up to date information when the user enters a new zone given by L=Tdet + Tload, where Tdet is the average time needed to detect the zone change, while Tload is the average time needed to retrieve and start provide the information available to the user. Since Tdet depends on the technique used to detect a zone change, hence, we will not consider following the contribution of Tdet to the latency, and focus on Tload.

Assuming the availability of a cache in the palmtop device, Tload can be expressed as

$$\text{Tload} = \frac{T_{rem}*M + T_{loc}(N-M)}{N} \quad (8)$$

where N is the average number of loading LDISs during the user utilize the service from localhost or remote server, M is the average number of cache misses experienced when the user utilizes the service, Trem is the time needed to retrieve and start loading the information from the remote server responsible for the information service, and Tloc is the time to retrieve and start loading information that is stored in a local cache of the mobile device (with Tloc << Trem).

As a measure of energy consumption, we decide to use the total time which the wireless interface of the mobile node is in active state (i.e. sending or receiving data). To carry out this measure, we must consider that the wireless interface is activated each time connecting to the remote server and must load the needed information. This event could be a cache miss, but could also be the correct updates to the cache content according to a given prefetching policy.

Reference shown in Fig. 10, when the palmtop access to the data of remote server, the overall average active time of the wireless interface can be expressed as follows:

$$T(i) = \text{Tsetup}(i) + \frac{D_{request}(i)}{W} + \text{Trem}(i) + \frac{D_{reply}(i)}{W} \quad (9)$$

If there exists m times of data transmission in route guidance, the overall average energy consumption can be expressed as follows:

$$\text{Ttot} = \sum_{i=1}^{m} T(i) \quad (10)$$

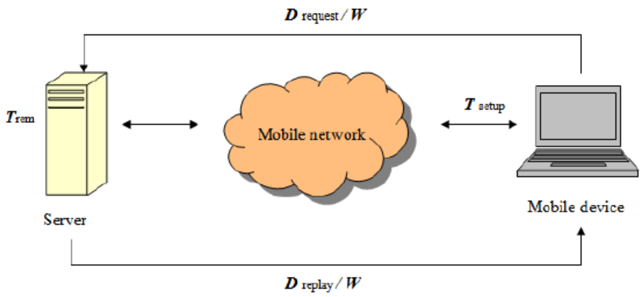

FIG. 10 THE OVERALL AVERAGE ACTIVE TIME OF THE WIRELESS INTERFACE

For example, when user1 travels to pass through 100 regions, and the probability of complete the whole system planning's route P_f is 70%, the probability of the linear direction P_s is 40%, and the probability of complete the system planning's route P_x is 80%. In addition, the direction of system planning's route is linear, but the user doesn't follow system planning's route because the route is not linear, which probability P_y is 25%. We also have considered Tsetup = 0.03s, Drequest = 200bytes, Trem = 5s, Dreply = 200Kbytes, W = 384Kbits. With these conditions in mind, we can discuss as follows:

1) Persone's Approach Performance

If we adopt Persone's approach that could derive Mper 、Nper – Mper and Nper, Mper is the number of the corners about the travel and equal to cache-miss K, Nper – Mper is the hit times of caching. It only loads ones the location-dependent information from the cache of the palmtop in perfect condition. Then, we could induce three variables as follows:

$$Mper = K$$

$$= 2L[(1-P_fP_s)–P_x(1-P_f)(1-2P_y)] \quad (11)$$

$$Nper – Mper = U(C_1) + U(C_{32})$$

$$= L[P_fP_s + (1-P_f)(1-P_xP_y)] \quad (12)$$

$$Nper = L[(2-P_fP_s)–P_x(1-P_f)(1-3P_y)] \quad (13)$$

We then use the numerals to substitute Mper = 120 times and Nper = 166 times. We use Mper and Nper to calculate information average latency Tload =3.628 seconds. From the formula (9), we could obtain the time cost which the mobile device is connected to the server T(i) = 9.201 seconds. After a period of time, if user1 has requested 120 times from the remote server, and the overall average active time of the wireless happens when interfacing Ttot = 1104.12 seconds.

2) *PPM-based Approach Performance*

If we adopt PPM approach that could derive Mppm 、Nppm – Mppm and Nppm, Mppm is the times of change within the travel and equal to cache-miss I, Nppm – Mppm is the hit times of caching equal to the user doesn't follow with complete system planning's path, Nppm is the total times of loading information equal to all regions. Then, we could induce three variables as follows:

$$Mppm = I = (1-P_f)*L \quad (14)$$

$$Nper – Mper = P_f*L \quad (15)$$

$$Nper = L \quad (16)$$

We can substitute Mppm = 30 times and Nppm = 100 times. Then, we use Mper and Nper to calculate information average latency Tload =1.535 seconds. From the formula (10), after a period time, when user1 requested 30 times from the remote server; therefore, the overall average active time of the wireless interfaces Ttot = 276.03 seconds.

In addition, we compare with the performance of two approaches on the expectation E(Xper) and E(Xppm), information average latency, and the energy consumption in Table II.

TABLE 2 THE PERFORMANCE OF TWO APPROACHES ON THE EXPECT VALUE, INFORMATION AVERAGE LATENCY, AND THE ENERGY CONSUMPTION.

E(Xper)	E(Xppm)	Tload of Persone	Tload of PPM	Ttot of Persone	Ttot of PPM
12.53	4.21	3.39	1.39	318.98	74.53
12.81	5.03	3.27	1.58	294.78	79.86
8.67	4.50	2.85	1.54	212.34	69.01
8.80	3.01	2.87	1.14	194.25	48.58
6.80	4.38	2.72	1.44	180.10	59.25
5.93	3.44	2.60	1.34	149.95	50.24
8.47	3.74	3.33	1.73	208.82	62.57
8.56	5.56	3.41	2.43	223.33	83.91
7.08	2.67	3.01	1.39	166.88	44.72
7.44	5.32	3.37	2.62	189.07	76.55
5.14	1.87	2.91	1.19	117.32	29.63
4.86	2.50	2.90	1.58	116.73	37.08
3.42	1.32	2.82	0.99	87.96	19.23
3.43	1.54	3.25	1.49	90.01	24.01
2.19	1.32	2.82	1.78	61.59	22.54
2.56	1.64	3.14	2.43	65.56	26.50
1.66	0.76	3.19	1.54	40.85	11.04
1.16	0.59	3.13	1.63	29.00	8.83
1.01	0.31	3.47	1.29	21.90	4.60
0.43	0.13	3.32	1.09	10.28	1.93

Experiments

Below we will explain our research the experimental environment, the procedure of the system simulation is described in the following chapter.

Experimental Environment

This experiment performed with the following platform; Pentium(R) D 2.80GHz CPU with Windows XP. Program used is JCreator Pro 3.5 and executed with Java. This platform is used to simulate the user's movement to generate PPM prefetching model, and through the model created to gather all necessary information required to compare the efficiency between PPM and Persone's strategy.

System Simulation Flow

In order to carry on the PPM information prefetching strategy which this research proposed, we have scheduled a set of system simulation flow, as shown in Fig. 11.

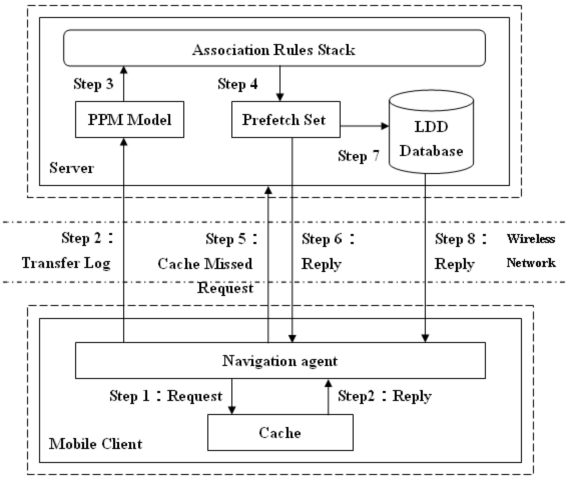

FIG. 11 SYSTEM SIMULATION LOGIC COMPOSITION

The simulation flow is as follows:

1. When the user initializes the navigation service, and input the starting point and destination, the navigation agent begins to request the related information, and cache these information.

2. At the same time, the agent will also transmit the content file for the remote server, which will establish or renew this user's individual PPM forecast model.

3.After individual the PPM forecast model is established, remote server will extrapolate rules to forecast the future potential behavior.(association rule)

4.When the related rule inferential reasoning completes, the information prefetching mechanism may rest on the confidence standard marginal value which we establish and decides the information prefetching set. System will fetch the information and deliver to prefetching set area (prefetching data set).

5. If the mobile device end takes in the memory area that doesn’t have the necessary data, which the agent requests promptly, usually occurs when a turn is made (cache-miss), the agent will send a request to remote server with the most up to date information.

6. After the server receives the request, the information prefetching set area has the necessary information. The information prefetching mechanism then capturing this data and the feedback is directly provided to the agent.

7. If information prefetching set area hasn’t got the information, the information prefetching mechanism (LDD database) sends out the request to server's related information bank, continuing to search in the information bank.

8. After the requested information is found, our information prefetching mechanism is given feedback based on this data. At the same time, the agent will also transmit this material the record files for the remote server, which will renew this user’s individual PPM forecast model.

Experiment of this research is divided into two parts, one is to use each user’s PPM model to carry on information prefetching; another part is when some regions the position related information, is unable to prefetch some user PPM model, we will carry on information prefetching PPM model for the user. After the experiment analysis stage, we will explain two partial the experimental results.

Experimental Result

We use the expected values about two approaches to compare with, the probability of the user complete system planning's route P_f is the important parameter, and discusses P_f to separate into 11 kinds of the situations the same as P_s、P_x、P_y. We represent the proportion of the user in completion with system planning's route and fails to comply with one to be a short form because it is convenient for our research, e.g., 0:10 representing the proportion of the user’s complying with system planning's route is 0.0 and doesn’t comply with one is 1.0. According to the property of the probability, there are 11 kinds in these combinations of the proportion. Equally, P_s、P_x、P_y are also the same as P_f. For compared with the Persone result, in the experiment process when the variable hypothesis can be controlled for and the same value.

For example, the running gear end writes down the information time T_{loc} = 10ms, server ends to write down the information time T_{rem} = 5s, running gear to the server to propose that the request material quantity size $D_{request}$ = 200bytes, running gear end links to the motion network's hypothesis time $T_{setup}(n)$ = 30ms. As well as, each region's position related

information size is 200Kbytes. What is only different, Persone hypothesis motion network bandwidth W = 200Kbits; This research nowadays considers the application way leads we direct the service and the main motion environment, therefore we establish the motion network bandwidth W = 384Kbits, may provide the highest dynamic bandwidth with the present mobile network to be the same.

From the Fig. 12-13, we adopt the PPM Match technology, which is used to predict the possible mobility of a user in his situation based on his past history of accessing, to prefetch the most useful information for the user in order to decrease the possibility of cache-miss. In our experiments, it has been shown that in most cases where our approach is more effective than that in the Persone's approach for improving the rate of cache-miss and the energy consumption.

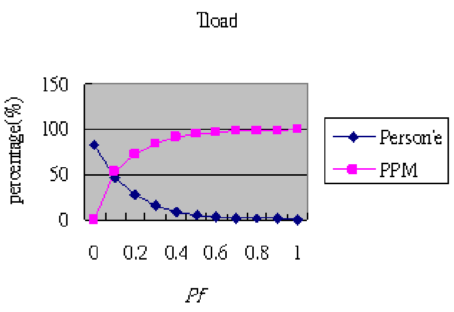

FIG. 12 BETTER PROPORTION OF TWO APPROACHES ABOUT PF ALL KINDS OF TLOAD.

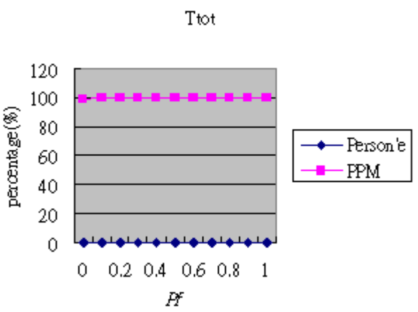

FIG. 13 BETTER PROPORTION OF TWO APPROACHES ABOUT PF ALL KINDS OF TTOT

Conclusions

We have proposed a systematic approach to conduct the individual mobility models for the related users with PPM. Based on the constructed models, the information for improving the quality of LDISs on a traveling route can be retrieved in a more effective arrangement. These results also can be used to improve the efficiency of energy consumption for mobile devices in which the energy is limited and valuable.

However, constructing the individual mobility models for the related users with PPM may have a large amount of time and storage consuming in the proposed method. We found the mobility models may be similar to some groups of users who interests are common. For example, some people always preferred the most short-path's from somewhere to their destinations. Hence, it may be a particular mobility model to serve this group of users. Further research can be implemented to categorize mobility trends of diverse mining groups.

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